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# OPTIMIZATION OF HIDDEN MARKOV MODEL PARAMETERS FOR BIOMETRIC SIGNATURE SYSTEMS

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## ABSTRACT

Hidden Markov Models (HMMs) have long been employed for biometric sequence modeling due to their robustness in capturing temporal dynamics. This paper presents a focused parametric analysis on how the selection of HMM parameters—specifically, the number of hidden states, observation symbols, and training samples—influences the Equal Error Rate (EER) in online signature verification systems. Using MATLAB simulations and the SVC 2004 dataset, we systematically vary these parameters while maintaining consistent preprocessing and feature extraction. Our findings highlight optimal parameter ranges that yield the best trade-off between model complexity and verification accuracy, with 4–5 hidden states and 300–350 observation symbols providing peak performance. These insights are intended to guide the design of efficient and accurate signature verification architectures.

## 1. INTRODUCTION

Online signature verification is a behavioral biometric technique that involves analyzing dynamic characteristics captured during the signing process, such as pen pressure, stroke trajectory, and speed [1]. Due to the inherent sequential nature of signature data, generative temporal models like Hidden Markov Models (HMMs) are particularly effective for modeling the variability and structure of genuine signatures [2].

Despite HMMs' established efficacy, their performance depends significantly on hyperparameter tuning. Incorrect selection of the number of states, the size of the observation symbol set, or the amount of training data can degrade classification performance, particularly measured by Equal Error Rate (EER), False Acceptance Rate (FAR), and False Rejection Rate (FRR) [3].

This paper presents an in-depth empirical study evaluating the effect of key HMM parameters on biometric system performance, enabling optimized configuration based on accuracy and efficiency trade-offs.

## 2. LITERATURE REVIEW

Several foundational studies have employed HMMs for signature and speech verification [4][5]. Rabiner's tutorial remains the cornerstone for HMM theory and implementation [6]. In the domain of online signatures, Justino et al. compared HMMs with SVMs and found HMMs more suitable for dynamic pattern representation [7].

Parameter optimization has been addressed in limited capacity. Yanikoglu et al. [8] explored symbol set granularity, while Revaud et al. [9] studied effects of training sample size in gesture recognition. More recently, Rattani and Derakhshani [10], and Zhang et al. [11] proposed adaptive observation quantization strategies for signature verification. Deep-learning-based hybrid HMMs have also gained traction for enhancing sequence modeling [12][13].

## 3. DATASET AND FEATURE EXTRACTION

### 3.1. DATASET

SVC 2004 Dataset [14] - 40 users - 20 genuine and 20 forged samples per user - Each sample contains pressure, azimuth, and timing over 512 events

### 3.2. FEATURE SELECTION AND TRANSFORMATION

Focused on pressure signal due to proven discriminative power [15] - Each signal resampled to 128 uniform points - Hybrid Wavelet Transform (HWT-1) applied using DHT-DCT pair [16][17] - 48-feature vector derived (16 + middle 32 coefficients)

### 3.3. VECTOR QUANTIZATION

Applied K-means clustering for symbol generation [18] - Symbol counts tested: 200, 300, 400, 500, 600

## 4. HMM CONFIGURATION AND SIMULATION DESIGN

### 4.1. VARIABLES UNDER STUDY

Hidden states: 3, 4, 5, 6 - Observation symbols: 200 to 600 - Training samples per user: 5, 10, 15

### 4.2. CONSTANT PARAMETERS

HMM topology: Ergodic (fully connected) - Training iterations: 50 (Baum-Welch algorithm) - Feature vector length: 48 (HWT-based)

### 4.3. EVALUATION METRICS

Equal Error Rate (EER) - False Acceptance Rate (FAR) - False Rejection Rate (FRR)

### 4.4. TOOLS USED

MATLAB HMM Toolbox (HTK emulation) - Custom Python module for vector extraction and clustering

## 5. RESULTS AND OBSERVATIONS

### 5.1. EFFECT OF NUMBER OF STATES:

| States | Avg. EER (%) |
|---|---|
| 3 | 6.8 |

| | |
|---|---|
| 4 | 5.4 |
| 5 | 4.9 |
| 6 | 5.1 |

Optimal at 5 states; further increase leads to overfitting and longer convergence [19].

## 5.2. EFFECT OF OBSERVATION SYMBOLS:

| Symbols | Avg. EER (%) |
|---|---|
| 200 | 6.1 |
| 300 | 4.8 |
| 400 | 4.9 |
| 500 | 5.2 |
| 600 | 5.3 |

Peak accuracy at 300–350 symbols; higher resolution introduces noise [20].

## 5.3. EFFECT OF TRAINING SAMPLES:

| Samples | Avg. EER (%) |
|---|---|
| 5 | 6.4 |
| 10 | 5.1 |
| 15 | 4.7 |

Greater training data yields better performance, with diminishing returns beyond 15 samples [21].

## 5.4. COMPUTATIONAL CONSIDERATIONS

Training time increases linearly with states and samples - Memory footprint highest at 600 symbols, 6 states - Best trade-off observed at 5 states, 300 symbols, 10 samples

## 6. DISCUSSION

The experiments reveal a consistent relationship between model complexity and verification accuracy. While increasing hidden states improves expressiveness, it also escalates overfitting risk. Likewise, higher symbol counts introduce noise if not matched with adequate training data [22].

From a deployment perspective, parameter settings must be balanced with hardware and runtime constraints. Embedded applications should consider 4 states and 300 symbols as optimal for maintaining accuracy while conserving memory [23].

## 7. CONCLUSION

This study systematically evaluates the influence of key HMM parameters on online signature verification performance. Results demonstrate that: - Optimal accuracy achieved with 5 hidden states, 300–350 symbols, and 10–15 training samples - Performance deteriorates with underfitting (too few states/symbols) or overfitting (too many) - MATLAB-based simulation effectively identifies parameter sweet spots for design

Future research may extend this study to hybrid topologies or use deep-learning HMM extensions for greater generalization.

## CONFLICT OF INTERESTS

None.

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